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Classification of Satellite Images by Texture-Based Models Modulation Using MLP Neural Networks

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(Abstract) The purpose of this paper is the automatic identification of various districts in satellite images using the textural feature, while comparing them by two methods of GLCM and Fourier Spectrum. The modulation of discrete violet and GLCM yielded a new method for the identification of the urban areas that is used as a criterion for measuring the development rate in the urban areas using satellite images. Through the modulation of GLCM and spatial features, this paper has presented an algorithm with a 9% of efficiency improvement as compared with the state where just the spatial features are being used. 26 features of GLCM have been used for the identification of dwelled areas. The problem of identifying various areas was analyzed by a new method and this method yielded desirable results. The results of simulation using MATLAB/IMAGE PROCESSING software on IKONOS database, from which the images have been collected, verify the accuracy of the performance of this system.

Keywords: Textural Features; GLCM Matrix; MLP Neural Network; Feature Vector; Satellite Images.

1. Introduction

Satellite images are being widely used in several fields of technology. Due to the abundance of the available data in this field, we need advanced automatic methods for extracting and providing the user with the required data out of these images. The Technical Committee of data extraction DFT is a subgroup of Land Remote Sensors team. Institute of Electrical & Electronic Engineers (IEEE) has been working on this field for many years and it has published several works including the most recent achievements of researchers in this field.

The problem investigated in this article is the automatic identification of various areas in a satellite image. These areas are selected based on the application of this article. GLCM matrix is one of the major elements in this study. GLCM matrix is a 2D matrix and the (i,j) element is the number of co-occurrences of i and j.

Many studies have been carried out so far on this topic and various methods have been presented by researchers. This research focuses on the application of textural features in the automatic identification.

2. Statement of the Problem

The geographists have been working on several urban areas on the map for a long time. It seems more essential than ever to have an intelligent and powerful system updated with urban development and improvements.

The techniques that process a wide area with a high speed and accuracy are highly needed, so the researchers are working on these techniques.

During the last decade, digital imaging tools have been progressed rendering it possible to view the surface of an area with its spatial and spectral details. Advanced aerial photography spectrometers are being increasingly used in various applications [2].However, the cost of the data received from these multi-spectral sensors is really high. The researchers with limited financial resources would not afford to observe the required data from high-frequencies. The next problem for multi-spectral aerial data is their high resolution which makes the feature identification, data processing, data extraction and object classification in the images quite difficult [2,3].This chapter deals with the analysis of the method suggested in this article and its advantages and disadvantages will be observed on various images. The input to this system is the satellite images collected from the source mentioned in [11] which is widely used as a source in most works on urban zones classification. These reference images are classified under the following categories: green space, street, highway, residential houses. Hence, we have four classes which should be called input images and the areas where these classes are located have to be identified.

The available images are used to train the neural system; therefore, these samples were selected so that they would be as different as possible. Through a considerable level of overlook, the neural networks can be called the electronic models of the neural system of human brain. The learning and training mechanisms of the brain is basically rooted in experience. An artificial neural network is an idea for data processing which has been inspired by the biological neural system and deals with data processing just like brain. These

images are used in this way: a feature vector is extracted from the images of each class and this feature vector is used for training the neural network. In other words, the neural network is trained to show the highway class at the output if the feature vector of this class was introduced as the input. A feature vector is obtained for each image and it corresponds to the same image. The program reads an image in every attempt and processes it to extract its feature vector. Another point considered in the collection of the neural network tutorial images database is the high number of its images, as the higher the number of tutorial samples the more the generalization possibility for the neural network. The other point is different sizes of images. The system is designed so that it would be able to work on all images with any sizes. When collecting the classes, the attempt was made to choose the images that are totally different in size.

The designed system enables us to easily increase the number of classes. Here, we have considered 4 classes; however, this system can be used for any number of classes.

3. The Suggested Method

3.1. General Algorithm of the Program

There is a general procedure for image processing and pattern identification: Training the neural network by the obtained feature vector. This research also uses a similar procedure as introduced here.

1) Reading the image available in Neural Network Tutorial Database;
2) Transferring the image from RGB to Gray Level;
3) Applying 3×3 averaging filter;
4) Formation of the feature vector for the input image;
5) Putting the total feature vector together and forming the final feature vector;
6) Formation of the target vector;
7) Structuring the neural network;
8) Training the neural network by the final feature vector and target vector.

Now, we will explain all these steps for the extraction of image.

To work with the available images, first all images should be read and processed one by one.

The input image is a colored image, or in other words, it has three dimensions of R, G and B. the features used in this research, as it will be explained in the following sections, have 2D matrices; therefore, the input colored image is transferred to a gray image in this step. The application of 3×3 averaging filter will visually result in the opacity of the image and, more precisely, the image buffers the neighboring pixels.

A) Elimination of very small noises, that appear as a beat on the output image, and edge detection;
B) Sometimes changes can be observed in the luminous intensity of the area that is being processed or there will be changes in the number of pixels. Through applying the averaging filter, a smoothing process is carried out on the number of pixels. The general efficiency of the system is highly significant and it increases the general classification percentage of the system.

A feature vector is obtained for every image and it corresponds to the same image. The program reads an image in every attempt and processes it and extracts its feature vector. Hence, we will have a feature vector for every image. Therefore, all these feature vectors have to be put together to form a more general vector. In this step, all feature vectors obtained from each image will form the general vector. This general vector will be used in the process of neural network tutorial [6].

To train the neural network, a vector is needed to specify the target of each feature vector. In other words, the target vector will specify the class of a feature vector related to the highway class. The training algorithm that is used for most neural networks is a supervised learning algorithm. The target vector has to be identified in this kind of training.

A neural network is structured based on the input vector and the target vector, in this step of neural network structuring. In this step, default values are considered for the neural network.

A highly significant issue for this step is deciding on the number of the hidden layer neurons and the number of layers. The trial and error method has been used in this study to find the best structure. We first started with a small neural network and the detection percentage was obtained. Then the neural network grew larger to achieve a desirable level. This step is one of the most important parts of this algorithm, because it adjusts the original classifier (neural network). Indeed, neural network tutorial adjusts the neuron weight values. The algorithm used for MLP neural network is back-propagation algorithm.

MLP network, as the name implies, is a set of neurons in several layers with each layer fully connected to the next one. After being multiplied by the available weight values, the input values reach the next neuron through the inter-layer pathways. There, the neurons are compiled and form the neuron output after passing through the related network function. Finally, the obtained output is compared with the desired output and the obtained error is used to correct network weights; this is verbally called neural network tutorial. The new idea dealt with in this research is the application of GLCM (Gray Level Co-Occurrence Matrix). Let us define GLCM first.

3.2. Definition of GLCM

Co-occurrence matrix is a matrix that is defined over an image. If the distribution of co-occurrence values are located in a specific offset, Matrix C will be defined over a $n \times m$ image with offset (Δx, Δy) parameters as follows:

$$C_{\Delta x,\Delta y}(i,j) = \sum_{p=1}^{n}\sum_{q=1}^{m}\begin{cases} 1 & \text{if } I(p.q) = i \text{ and } I(p+\Delta x, q+\Delta y) = j \\ 0 & \text{otherwise} \end{cases}$$

Co-occurrence matrix is a statistical method that can extract the second-order statistics in a textural image. Another

definition that can be offered for GLCM is that: GLCM is a 2D histogram in which the (i,j) element refers to the co-occurrences of i and j. Co-occurrence matrix is identified in two pixels by relative frequencies of $P(i,j,d,\theta)$, if these two pixels are located in the distance of d and direction of θ, one with the brightness of i and the other with the brightness of j. Hence, GLCM is a function of the distance of r and angle of θ and the brightness of i and j. We should look for appropriate r and θ, when identifying the letters.

When GLCM matrix is estimated, the features should be extracted from the matrix. As this matrix cannot be directly given to neural network classifier as a feature vector, some mathematical operations have to be performed on GLCM. These mathematical operations are known as feature extraction from GLCM. Some of these features are mentioned here.

1) Mean GLCM:

$$f_1 = \frac{p(i,j)}{\sum_j p(i,j)}$$

2) Contrast:

$$f_2 = \sum_i \sum_j (i-j)^2 p(i,j)$$

3) Entropy:

$$f_3 = \sum_i \sum_j \left(\frac{p(i,j)}{\log p(i,j)} \right)$$

4) Angular Second Moment:

$$f_4 = \sum_i \sum_j p(i,j)^2$$

5) Homogeneity

$$f_5 = \sum_i \sum_j \left(\frac{p(i,j)}{1+|i-j|} \right)$$

6) Dissimilarity

$$f_6 = \sum_i \sum_j |i-j| p(i,j)$$

7) Correlation

$$f_8 = \sum_i \sum_j \frac{(i-\mu_x)(j-\mu_y)p(i,j)}{\sigma_x \sigma_y}$$

8) Energy

$$f_9 = \sqrt{\sum_{i=0} \sum_{j=0} p^2(i,j)}$$

These features, as implied by their relations, yield a number of a GLCM and they are appropriate for the production of feature vector.

GLCM, as mentioned earlier, can express the way of distribution of pixels values, through appropriate selection of d and θ. It is more common in GLCM works to use the vector form instead of d and θ. For example instead of $d = 1$, and $\theta = 45^o$, we will write offset=[1 1]. Figure 1 shows this concept schematically.

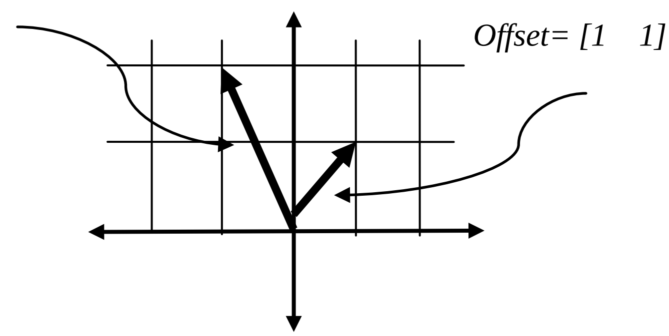

Figure 1. Vector Expression of d and θ in the definition of GLCM

Therefore, the selection of offset parameter will significantly influence the results obtained from the application of GLCM, because it shows the way of its formation.

In this research, the image was first divided into 7×7 windows. In other words, we transfer the input image matrix to 7×7 matrices. Then, 12 matrices will be estimated for four distances $d=2,3,4,5$ and angles of $\theta=0, 45, 90$. All offsets are shown in table 1.

Table 1. All offsets used in this research for GLCM

[2,2]	[0,2]	[2,0]
[3,3]	[0,3]	[3,0]
[4,4]	[0,4]	[4,0]
[5,5]	[0,5]	[5,0]

When 12 GLCM of 7×7 windows are estimated, the feature extraction will be followed. 5 features of correlation, angular second moment, dissimilarity, homogeneity and energy will be obtained from each matrix. Therefore, 15 features will be achieved for every line of table 1 and the total number of 60 features will be obtained for table 1.

4. Simulation Result

Here, the results of implementation of the algorithm, that was defined in the earlier sections, will be discussed. The database where the images were collected from is called IKONOS [11]. This database is one of the most well-known databases used in most essays on Images. One of the most significant features of the images of this database is the high resolution of images. High quality is not available in all databases. This feature has

made the database distinguishable. Another fact related to the images of this database is the aerial images of urban areas.

Figure 2. An image from the database.

Figure 2 illustrates one of the images available in the database. We will use this image here to show the results obtained from the algorithm. First, as it was mentioned earlier, the visual sample will be collected from each class. The number of samples of each class is shown in table 2. The neural network used in this section is obtained from MLP simulation. There are 60 input neurons in the neural network and there are 35 hidden layer neurons and 4 output layer neurons. Tangent-sigmoid transfer function is used to transfer several layers.

Table 2. The number of samples of each class

Class	Tree	Street	Highway	Residential houses
Number	30	20	44	44

After training the neural network, the system should be tested by an image. Figure 3 is an image that is used to test a system. After training the neural network, the error criterion value is changed as follows and it will tend toward zero (figure 4).

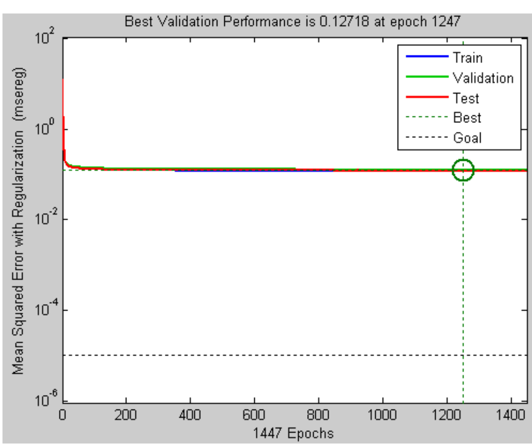

Figure 3. Change of error criterion during neural network tutorial

The blue color in the following images illustrates the residential houses, orange shows highways, red shows street, and green shows green spaces. The number of neurons of hidden layer was changed to 50 neurons in an experiment and the results were obtained. Figure 4 shows input image of this experiment and figure 3 illustrates the results obtained.

Figure 4. The image of testing the general system for hidden layer neurons of 20 and 50.

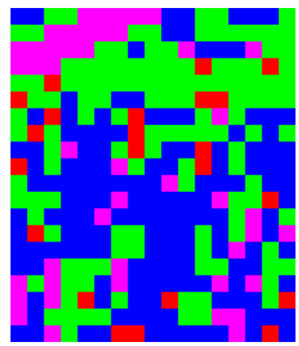

Figure 5. The result obtained from the hidden layer with 50 neurons.

In another experiment, the number of neurons of the hidden layer was changed to 20 and the results were obtained. Figure 4 illustrates the input image of this experiment and figure 6 illustrates the result of it.

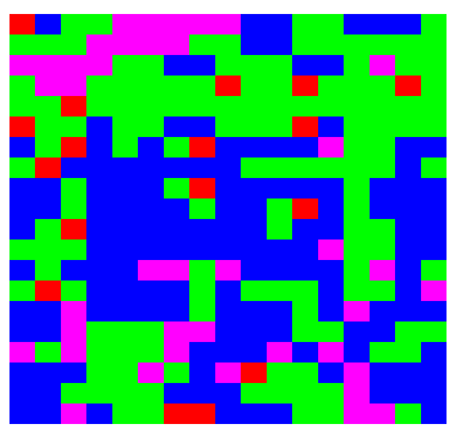

Figure 6. The results obtained from the hidden layer with 20 neurons.

6. Conclusion

The textural analysis plays a significant role in digital image processing and its expression, and it can provide us with the extra data for working on the satellite images. Using the concept of texture, we came to this concept that the area of different zones on satellite images has different textures. Then, the co-occurrence matrix was used to obtain the features of these regions. The extracted features include: dissimilarity, angular second moment, correlation, energy and homogeneity. Four classes of residential houses, highways, street, green space were considered in this study. The results reveal that MLP neural network has the best efficiency.

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